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Lawrence Livermore National Laboratory

Bayes-Adaptive Interactive POMDPs

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Team

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Talk outline

- Goal
- Motivation
- Example applications
- Assumptions and strategies
- Single-agent decision process (POMDP)
- Interactive decision process (IPOMDP)
- Bayes-adaptive interactive decision process (BA-IPOMDP)
- Concluding remarks

Goal

- ***Advance modeling and response against human-like agents*** who seek to actively "game" against each other over the course of repeated interactions

- Build from current theory in artificial intelligence
  - Sequential decision-making frameworks

- "Bridge the gap" between theory and practice to solve real-world adversarial problems

Motivation

- Humans analyze many factors before acting
  - Current status
  - Opponent behavior
  - Past strategies (opponent and self)

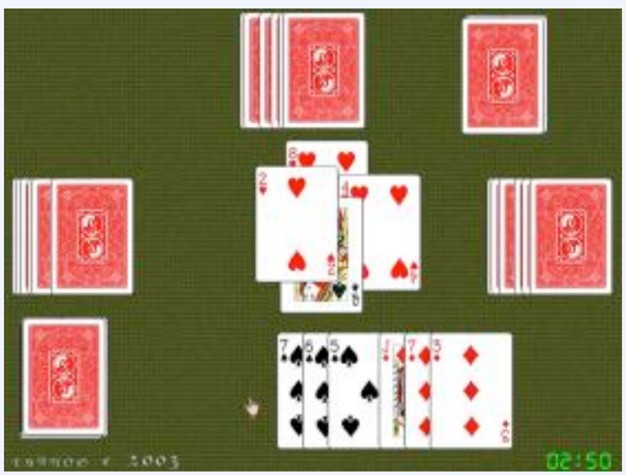
- Drawbacks in traditional game theory (Nash equilibria)
  - No clear way to choose between multiple equilibria
  - Inability to deal with opponents that do not act according to equilibrium strategies

Can we develop computer systems that process decisions more like we do?

Assumptions and strategies

- Uncertainty about the (non-deterministic) environment
- ➢ Maintain belief, or probability distribution, over states

- Example: card games



Assumptions and strategies

- Intelligent opponents (who also maintain beliefs about us)
  - Account for the opponent's beliefs in *nested* models; more uncertainty inherent in more deeply nested beliefs

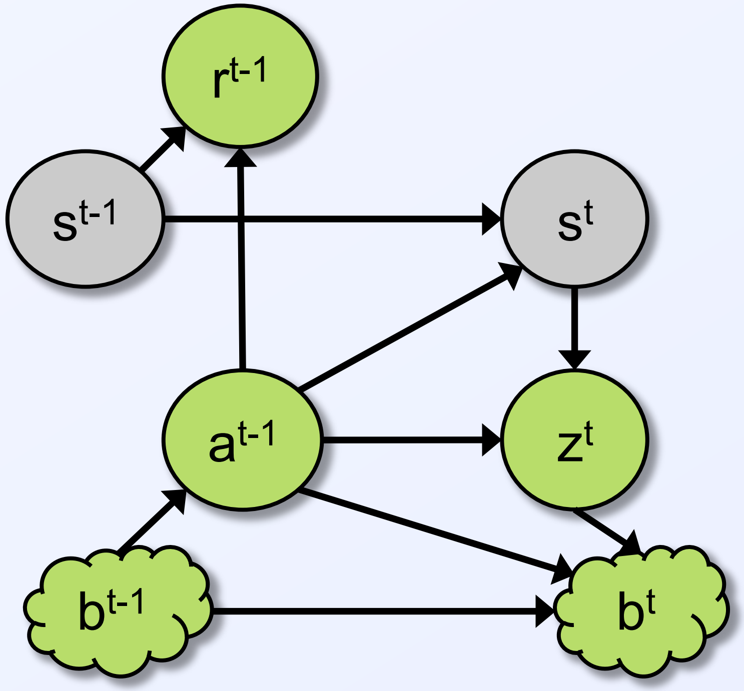
Assumptions and strategies

- Uncertainty about the effects of actions
  - Not entirely certain about how:
    - Environment state changes as a result of actions
    - Observations are related to environment state

- Treat transition model and observation model as part of the uncertain environment state
- Maintain beliefs over model parameters (in addition to the environment states)

To develop our model, we start with the single-agent decision process… the POMDP

- A *single-agent decision process* at each time step involves:
  - *s* : state of the environment, unknown to the agent
  - *a* : action that the agent performs
  - *r* : reward due to current state and current action
  - *z* : observation due to current state and previous action



Background: POMDP

- Common framework for planning in single-agent domains

$$POMDP = \langle S, A, T, \Omega, O, R \rangle$$

  - States S
  - Actions A
  - Transition function $T : S \times A \rightarrow \Delta(S)$
  - Observations Ω
  - Observation function $O : S \times A \rightarrow \Delta(\Omega)$
  - Reward function $R : S \times A \rightarrow \mathbf{R}$

Background: POMDP

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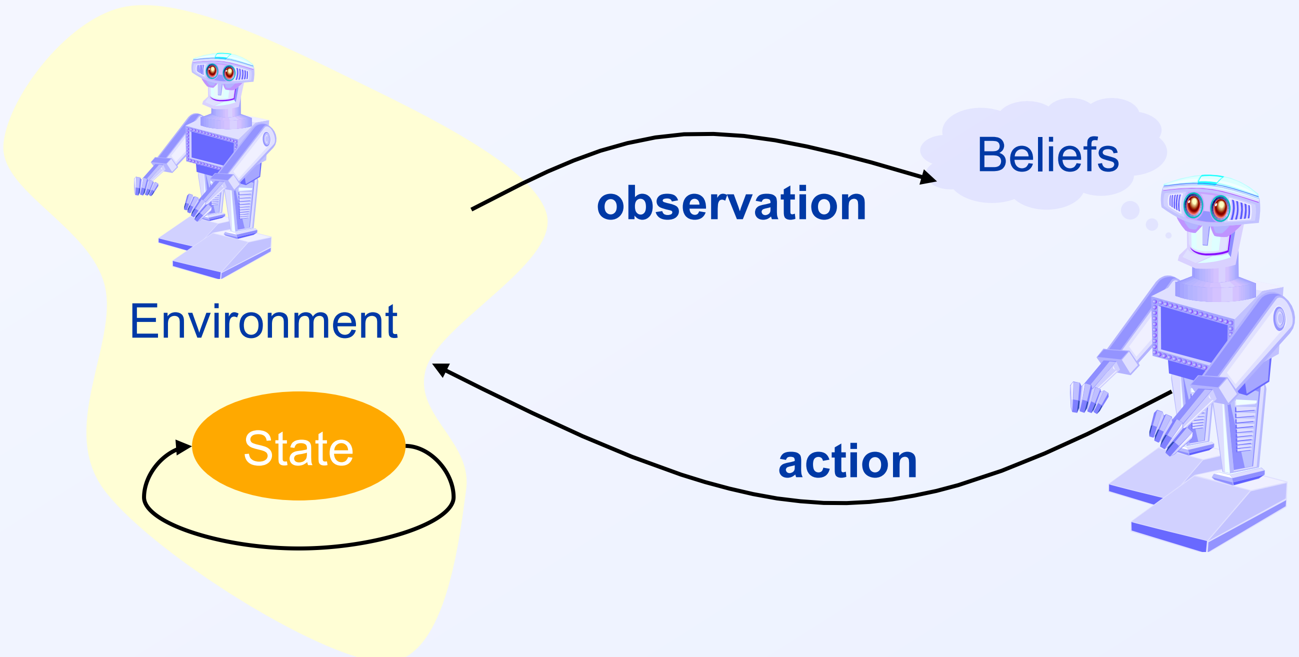
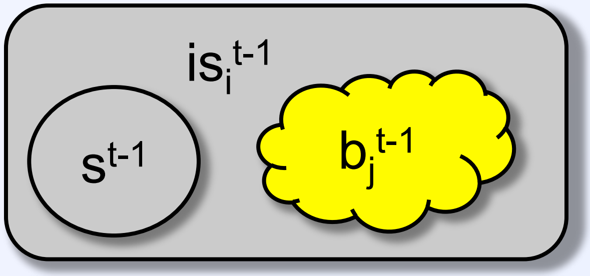


Agent's objective: optimize rewards given its beliefs

For adversarial modeling, we need an *interactive* decision process… the IPOMDP

- An *interactive decision process* involves (at least) two agents; their joint actions affect the next state.
- Each agent has its own *interactive states (is)*, with nested beliefs to predict the opponent's action.



Background: IPOMDP

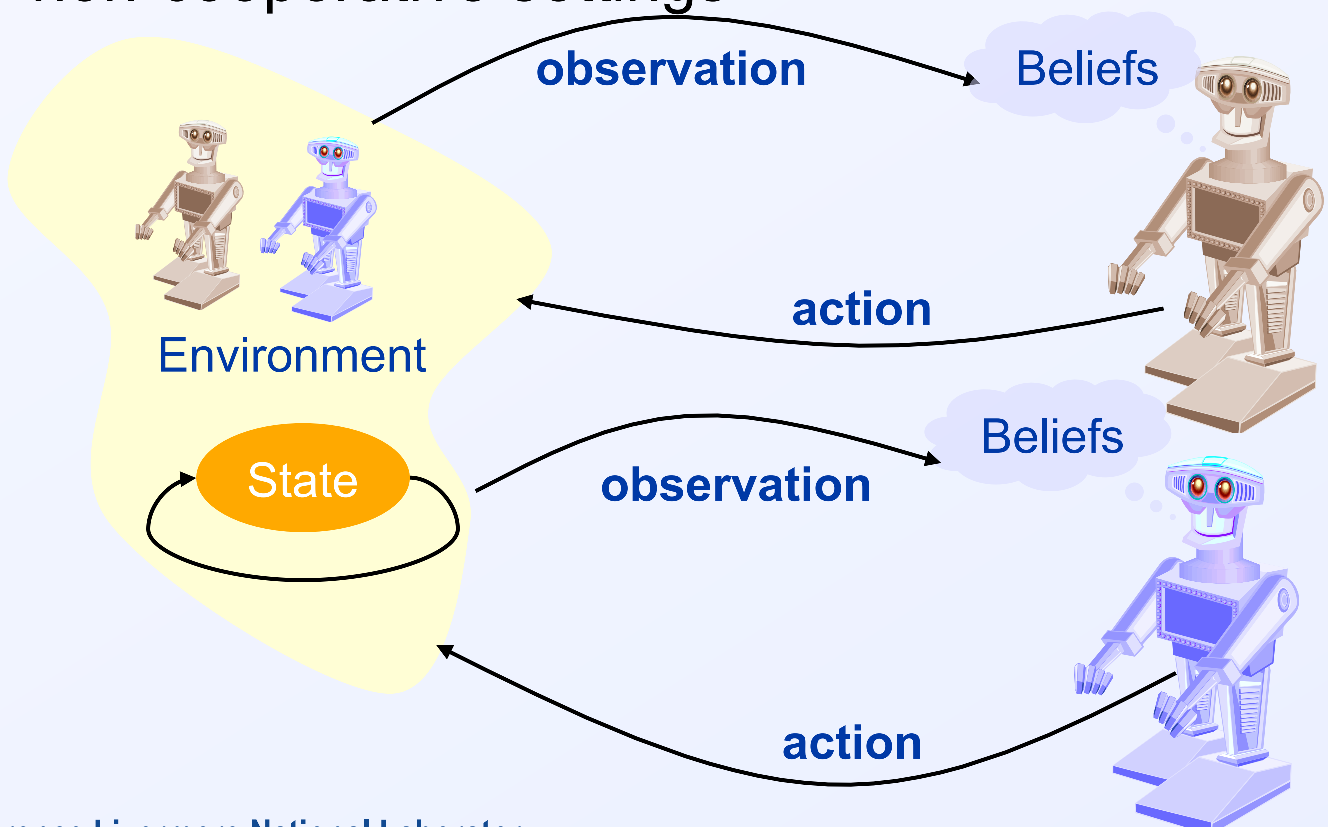
- Multi-agent extension of POMDP
- Supports decision-making in both cooperative and non-cooperative settings

$$IPOMDP_{i,l} = \left\langle IS_{i,l}, A, T_i, \Omega_i, O_i, R_i \right\rangle$$

- Interactive states $IS_{i,l} = S \times M_{j,l-1}$ with $IS_{i,0} = S$
- Joint actions $A = A_i \times A_j$
- Transition function $T_i : S \times A \rightarrow \Delta(S)$
- Observations Ω_i
- Observation function $O_i : S \times A \rightarrow \Delta(\Omega_i)$
- Reward function $R_i : IS_i \times A \rightarrow \mathbf{R}$

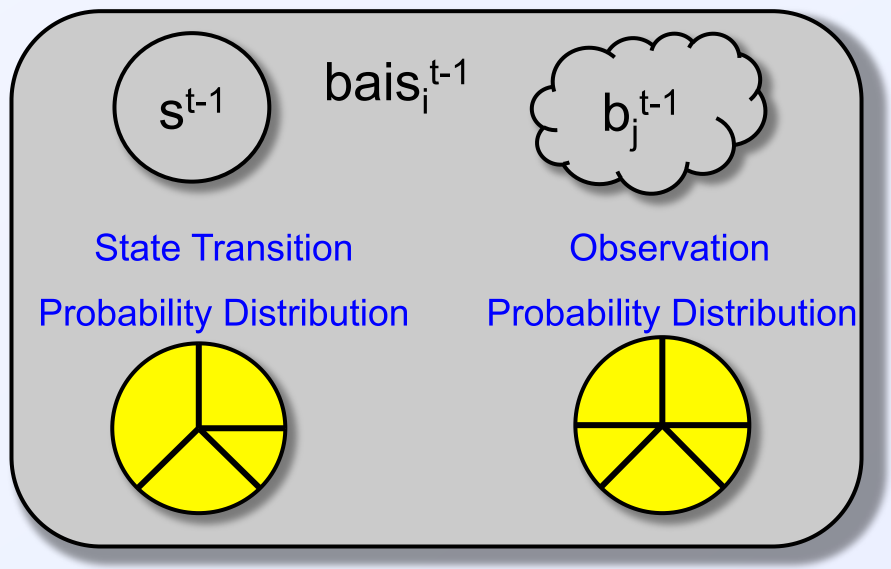
Background: IPOMDP

- Multi-agent extension of POMDP
- Supports decision-making in both cooperative and non-cooperative settings



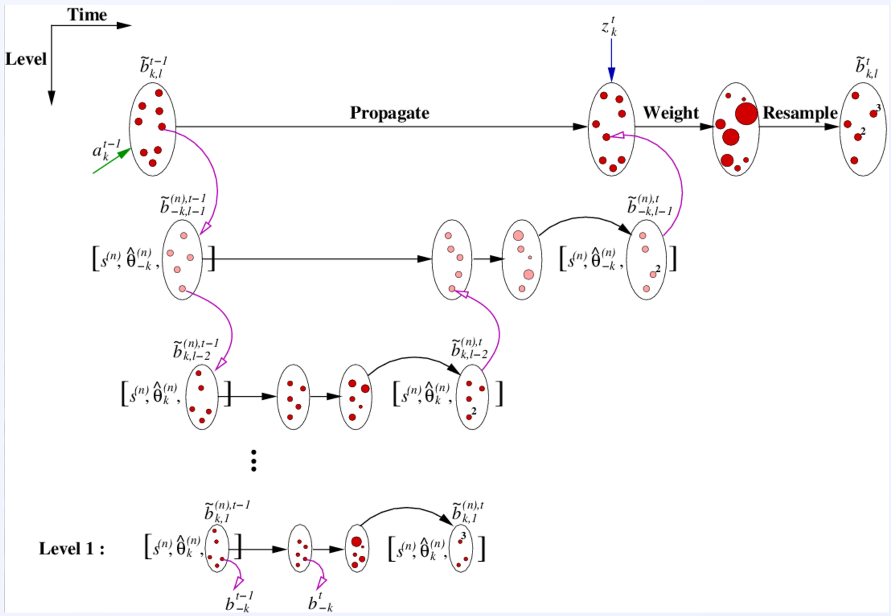
To increase realism, we came up with an adaptive interactive decision process… the BA-IPOMDP

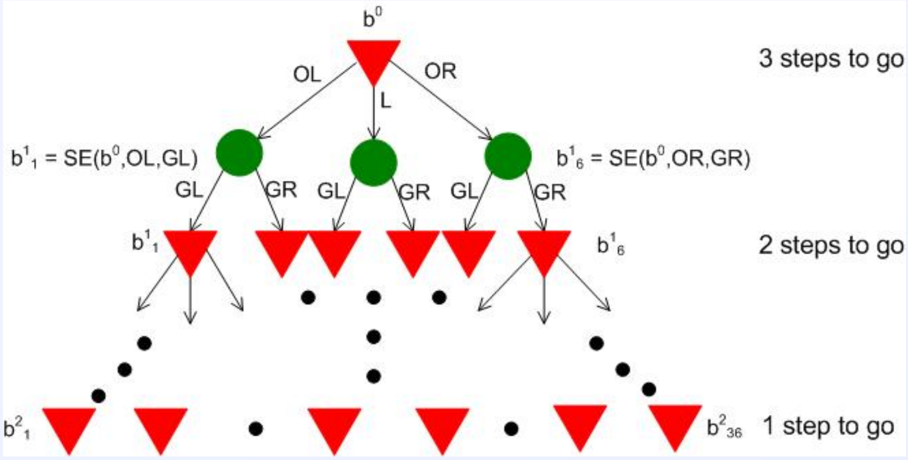
- A *BA-IPOMDP* allows uncertainty to be associated with the transition and observation functions via "augmented" *Bayes-Adaptive interactive states (bais)*.
- A *bais* contains counts on previous state transitions and observations.
- The counts define the expected probabilities for T and O.



A number of computational challenges exist in solving a BA-IPOMDP

- Nested beliefs can lead to exponential increase in runtime for belief update
- Huge state space due to counts being part of the state
- Reachability trees with large branching factors



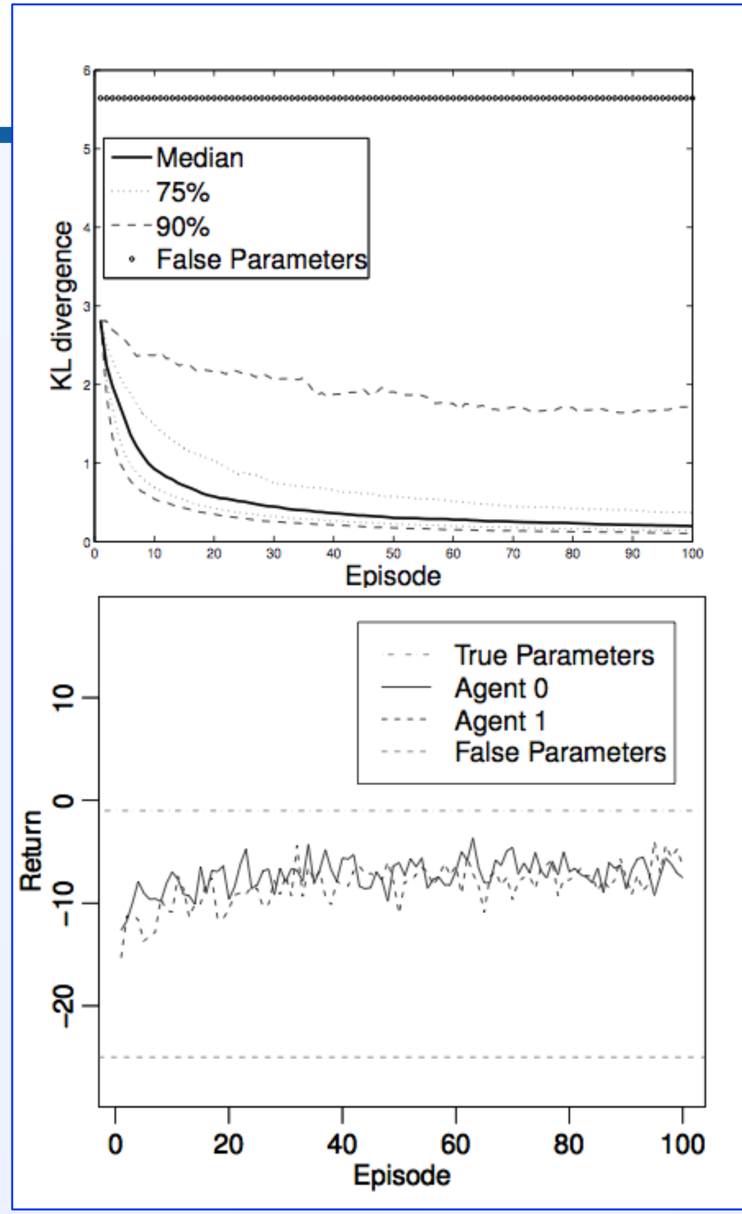


Simulation experiments: multi-agent tiger problem

- Two rooms/states: ferocious tiger in one room, jackpot in the other.
  - Tiger position resets when a door is opened.
- Three actions: {open left door, open right door, listen}.
- Six observations: {growl from left side, growl from right side} × {door creak from left side, door creak from right side, silent}.
- Rewards: -100 for opening the tiger's door, +10 for opening the pot of gold's door, -1 for listening.

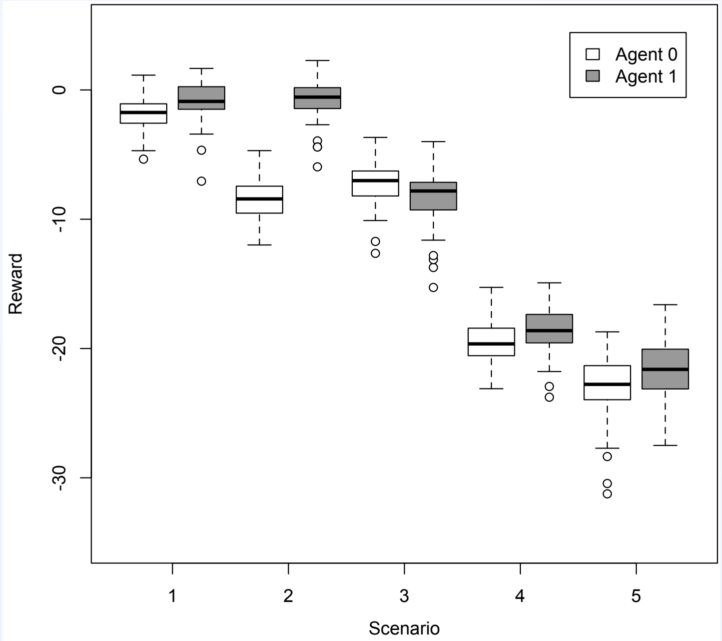
Results

- Learned values for observation probabilities converge to actual values.
- Learning agent earns more rewards than non-learning agent with incorrect assumptions.



Results

Scenario	Agent 0		Agent 1	
	Self	Opp.	Self	Opp.
1	Learn	Correct	Correct	Correct
2	Learn	Learn	Correct	Correct
3	Learn	Correct	Learn	Correct
4	Learn	Incorrect	Learn	Incorrect
5	Learn	Learn	Learn	Learn



- Learning agents take more conservative actions, thus earn less rewards than non-learning agents.

Concluding remarks

- The POMDP and its extensions provide a natural way to model sequential decision-making under uncertainty
- Major advances made in applying AI theory to real-world problems (mostly coordination between cooperative agents)
- In theory, proposed framework shows promise for modeling complicated human adversarial systems
- In practice, deployment currently hindered by algorithmic complexity

For technical details and references, please refer to our AAAI paper.